Unequal Hiring Wages and their Impact on the Gender Pay Gap

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Abstract

National payroll earnings data reveal that men are generally paid more than women when they enter firms. Although this hiring wage gap has narrowed over the past two decades, it still accounts for over half of the overall gender pay gap in Great Britain. Even when firms hire men and women into the same specific occupation at roughly the same time, and accounting for previous work experience, there remains an unexplained hiring wage gap within jobs that favours men by 2.6%. These findings suggest that gender pay gap reporting laws that focus exclusively on the overall gaps within employers miss an important margin. Mandating employers to additionally disclose their wage gaps among newly hired workers could be highly informative.

Keywords: Gender segregation, Occupation-specific wages, Employer-employee data
JEL codes: J16, J31, J70

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1. Introduction

Within most industrialised countries, gender differences in wages have tended to fall substantially over the last century. However, this convergence has stalled in recent decades, leaving sizeable gaps (e.g., Blau and Kahn, 2017; Olivetti and Petrongolo, 2016). At the same time, mounting evidence shows that women still have significantly lower hiring wages than the directly comparable men who start alongside them in new jobs (e.g., Roussille, 2024; Säve-Söderbergh, 2019). Given the high levels of job turnover and switching within labour markets, women's lower hiring wages, rather than slower pay progression within jobs compared to men, could explain the persistence and large parts of the remaining gender wage gaps (Kunze, 2018). In this paper, we use accurate payroll-based and nationally representative employer-employee data from Great Britain to examine whether unequal wages at the hiring margin can explain the ongoing persistence of the gender pay gap.

We make several contributions to the gender pay gap literature. First, we propose a decomposition of the national wage gap into differences between men and women in wages when they start to work for a new employer, in wage growth within the same employer, and in the likelihood of staying with an employer, building on earlier work by Manning and Robinson (2004). This offers a *dynamic* view on the determinants of the gender wage gap, emphasising the importance of search frictions and complementing the standard approach that explains the gap by analysing cross-sectional averages. When averaging across all age groups, we find only minor gender differences in retention rates and wage growth within employers. In contrast, the hiring wage gap is sizeable and, based on current patterns, explains more than two-thirds of the long-run (steady-state) gender difference in hourly earnings in Great Britain. Intuitively, because every employee was hired at least once at some point, and within-employer wage growth and employee retention rates do not differ much by gender in the aggregate labour market, initial differences in hiring wages persist and accumulate with every additional employer switch throughout a worker's career. Additionally, we find that gender differences in hiring wages have almost completely ceased converging over the most recent decade in Great Britain, offering another perspective on why progress on closing the overall gender wage gap has stalled. While being cautious about drawing any conclusions on causality, as with all wage inequality decompositions, our results provide some valuable new insights into the sources of the gender pay gap. Our findings add to the literature on the emergence of the early-career gender pay gap, which typically shows a prominent role for within-employer wage growth differentials during the first years in the labour market (e.g., Barth, Kerr, and Olivetti, 2021; Bertrand, Goldin, and Katz, 2010; Manning and Swaffield, 2008).[1] By additionally analysing mid and late-career employees, we provide a complementary and more comprehensive picture of the aggregate sources of the gender wage gap.[2]

When employers have some control over what pay they offer a new worker, two factors can influence the average hiring wages of women differently compared to men: whether employers and occupations that typically pay higher wages are more or less likely to hire women, and whether employers offer different hiring wages to men and women for the same job. We examine both of these factors in turn. First, we assess the extent to which gender segregation into high-wage employers and detailed 4-digit occupations can account for the observed overall hiring wage gap. This analysis is the second main contribution of our paper, adding to the extensive literature on the importance of segregation for the overall gender wage gap. For example, several studies have shown that women are more likely to work in low-paying occupations (e.g., Groshen, 1991; Macpherson and Hirsch, 1995). More recently, Blau and Kahn (2017) find that the share of the United States gender wage gap accounted for by the gender segregation of occupations and industries increased to almost 50% in 2010. Likewise, some authors find evidence of female segregation into low-paying employers (e.g., Sorkin, 2017, for the United States, Heinze and Wolf, 2010, for Germany, and Jones and Kaya, 2023; Mumford and Smith, 2009, for Great Britain). Finally, some studies provide evidence for

[1] Manning and Swaffield (2008) find that differences in early-career wage growth rates substantially favour men in the United Kingdom. In the United States, Barth, Kerr, and Olivetti (2021) also find that within-employer wage growth differentials are the main drivers of the gender wage gap during the first years in the labour market. However, women's within-employer wage growth outpaces men's ten years after first entering the labour market. Del Bono and Vuri (2011) show that gender differences in the returns to job mobility are the primary driver of gender earnings growth differentials in Italy. By contrast, Bronson and Thoursie (2021) find that within-employer wage growth, rather than between-employer, mainly accounts for the early-career gender wage gap in Sweden.

[2] Our emphasis on hiring or entry wages also aligns with evidence that declining the gender pay gaps in the US, UK, Canada, and Italy of late have been primarily cohort-driven; each new cohort of workers enters the labour market with a smaller gender pay gap than the one that exits (Arellano-Bover et al., 2024).

the importance of gender segregation at the occupation-employer level in explaining existing gender wage gaps (e.g., Bayard et al., 2003, for the United States and Card, Cardoso, and Kline, 2016; Cardoso, Guimarães, and Portugal, 2016, for Portugal, and Jewell, Razzu, and Singleton, 2020, for Great Britain). Extending this previous research with the first national evidence at the hiring margin, we find that gender segregation into high-wage employers and occupations explained over 60% of the hiring wage gap in Great Britain in the few years before the financial crisis of 2008-09. However, in recent years, before the COVID-19 pandemic, this segregation can explain just over 40% of the hiring wage gap; most of the differences between men's and women's hiring wages appear to occur within the same employer and the same narrowly defined occupations.

Our third contribution is to study the second factor that influences the average hiring wages of women compared to men: we provide the first comprehensive analysis of differences in hourly hiring wages between men and women who are hired together into the same occupation by the same employer within the same year, hereafter what we call a *job*. Once we control for new hires' experience and working hours, there remains a statistically and economically significant residual or unexplained hiring wage gap of 2.6% within jobs. The largest difference appears in the highest quartile of the hiring wage distribution, where the hiring wages of men exceed those of women by 4.6% in the same job. We also find that employees who earned a higher wage in their previous jobs earn more than their fellow new hires in the next job, consistent with the results of a recent field experiment by Barach and Horton (2021). Further, the effect of past wages appears to be generally significantly smaller for women, creating a path dependency in the hiring wage gap. However, there is no evidence that this is the case within professional jobs or where some form of collective agreement covers pay. This evidence provides an important addition to the findings in Card, Cardoso, and Kline (2016) and Sin, Stillman, and Fabling (2022) that women receive a lower share of employer-specific pay premiums. Säve-Söderbergh (2019) studies a sample of college graduates in the social sciences in Sweden, finding that women state salary requests more frequently than men do. However, those women were asking for lower salaries and, even when making requests otherwise comparable to men's, were offered lower starting salaries. Relatedly, Biasi and Sarsons (2022) find that a reform increasing pay flexibility among public school teachers in Wisconsin lowered women's salaries compared with men, partly driven by women engaging less frequently in pay negotiations. However, Exley, Niederle, and Vesterlund (2020) provide evidence that women only enter negotiations that result in gains, avoiding negotiation opportunities that would result in losses. While we do not directly analyse any of these underlying reasons, our study provides novel evidence about hiring wage differentials based on accurate employer payrolls and a nationally representative sample of workers, occupations, and jobs over a much extended period.

In a closely related study, Roussille (2024) analyses data from an online recruitment platform for highly educated candidates in the tech industry. Roussille documents an ask-gap of 2.9%, adjusting for differences in observable characteristics, consistent in magnitude with our estimate of an unexplained within-job hiring wage gap for Great Britain of 2.6%. Compared to this study, ours offers at least two important advantages: First, while Roussille (2024) considers only a single, high-income occupation, we analyse a much more nationally representative sample of workers. As such, we can assess the impact of gender segregation in employers and occupations throughout the labour market on hiring wages, and provide results covering low-paid workers. Second, our data span multiple years, allowing us to study the evolution and dynamic behaviour of the gender gap in hiring wages.

The British payroll dataset, the Annual Survey of Hours and Earnings, has unique features that make it ideally suited for our study. First, we observe when employers hire men and women, allowing us to abstract from employer-specific wage premiums and any sorting by gender in that regard as a determinant of the overall gender wage gap in Great Britain (Jewell, Razzu, and Singleton, 2020). Related, there is growing evidence that women may select into and have a greater willingness to pay than men for jobs that offer flexible working (e.g., He, Neumark, and Weng, 2021; Mas and Pallais, 2017), which may in part explain the accumulation of gender earnings gaps over the lifecycle (e.g., Kleven, Landais, and Søgaard, 2019). Looking within jobs in ASHE, we can largely abstract from these potential broader causes of residual gender pay inequality and focus on wage differences at hiring. Second, employers are legally obliged to report employee earnings according to their payrolls, making the dataset more accurate than those obtained from household surveys (Nickell and

Quintini, 2003). Third, the dataset has a large sample size, with approximately 200,000 employee observations annually. This size allows us to match a large number of new hires by year, employer, and specific occupation within the employer. Fourth, the dataset contains detailed data on 4-digit occupations (e.g., "Housekeepers" vs. "Waiters or waitresses" in a hotel) and the date an employee started working at their employer, all of which are necessary for analysing hiring wages within employer-occupation-year (or 'job') cells. Fifth, unlike most administrative datasets used in previous research, the ASHE provides hours worked, allowing us to compute hourly wage rates. Furthermore, these are reported by employers rather than workers, addressing any concern that the observed gender wage gap in some datasets might be partially explained by differences in how men and women report their hours relative to what is contracted or actually worked. Finally, earnings in the dataset are not top-coded, allowing us to consider that wage income is right-skewed and top earners are more likely to be men.[3]

The rest of the paper is structured as follows: Section 2 describes the Annual Survey of Hours and Earnings and our estimation sample selection; Section 3 introduces our decomposition method for the overall gender wage gap; Section 4 discusses the relative contribution of hiring wages to the overall gender wage gap; Section 4 also presents estimates on the role of gender segregation across employers and occupations in hiring wages; Section 5 presents estimates of the hiring wage within jobs, its determinants, and discussed extensions and robustness checks; and Section 6 concludes.

2. Data and Descriptive Statistics

The Annual Survey of Hours and Earnings (ASHE) (Office for National Statistics, 2024) is a longitudinal, linked employer-employee dataset that began in 2005. The data are based on a one per cent random sample of British employees who pay income tax or make National Insurance contributions. Employers are legally obliged to respond to the survey questionnaire sent to them. Information is provided concerning the pay period that includes a specific survey reference date in April. The design of the ASHE implies that data are only available for

[3]See, for example, Fortin, Bell, and Böhm (2017) for an insightful discussion of examining the gender pay gap when incomes are top-coded, using the same ASHE dataset as ourselves.

individuals employed on the survey reference date. The longitudinal aspect of the ASHE allows us to track employees over time and link them to their respective employers using the provided employer identifiers.[4] Hereafter, we frequently use the more common term 'firm' instead of 'employer' or 'enterprise', which refers to a UK-specific administrative definition of an employer that could contain several local units or plants.

Our preferred wage measure is gross earnings per hour, excluding overtime, hereafter the *wage*. The UK Office for National Statistics (ONS) uses the ASHE data and gross earnings per hour, excluding overtime, to derive the official national statistics on the gender pay gap.[5] Earnings include all basic pay, premium payments for shift, night, and weekend work, incentive pay for work carried out in the pay period, and any pay received through payroll for other reasons, e.g., meal allowances. We also analyse basic earnings per basic hour worked, hereafter the *basic wage*, to assess the impact of the extra pay components on gender differences in pay. We adjust all nominal wage variables in the ASHE to 2002 pound sterling prices using the UK Consumer Price Index in April, also published by the ONS.

Employers provide information for ASHE that indicates an employee's occupation up to the detailed 4-digit level according to the UK Standard Occupational Classification (SOC) 2000 between 2005-2010 and its slightly updated version, SOC 2010, from 2011 onward.[6] Our analysis below uses occupational categories at the 3-digit (minor groups) and 4-digit (unit groups) levels. SOC 2000 uses 81 and 353 categories at the 3-digit and 4-digit levels, respectively, while SOC 2010 uses 90 and 369 categories at the 3-digit and 4-digit levels, respectively. According to SOC 2000, examples of 3-digit occupations and their associated 4-digit occupations are SOC 322 "Therapists"; SOC 3221 "Physiotherapists"; SOC 3222

[4]The information in our dataset about the characteristics of employers comes from the UK's Inter-Departmental Business Register, the official list of UK enterprises. Employers in the ASHE are typically enterprises, as defined for UK government administrative purposes: The smallest combination of legal units that is an organisational unit, which benefits from a certain degree of autonomy in decision-making, especially for allocating its current resources. Employers include all private, public, and voluntary sector employers.

[5]For the official figures on the UK gender pay gap see https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningsandworkinghours/bulletins/genderpaygapintheuk/2023

[6]For information on the UK SOC 2000 and SOC 2010, see https://www.ons.gov.uk/methodology/classificationsandstandards/standardoccupationalclassificationsoc/socarchive and https://www.ons.gov.uk/methodology/classificationsandstandards/standardoccupationalclassificationsoc/soc2010, respectively.

“Occupational therapists”; SOC 3223 “Speech and language therapists”; and SOC 3229 “Therapists not elsewhere classified”.

We study employees aged 16-64 who did not incur any loss of pay in the April reference period (e.g., unpaid sick leave) and were not paid at an apprenticeship or a trainee rate. We exclude a small number of person-year observations in which a worker held multiple jobs, was reported as having worked on average less than one or more than 100 hours per week in April, was reported as being paid less than 80 per cent of the age-relevant statutory National Minimum Wage, or had missing or imputed values for any of the pay variables that we are interested in. Besides the recorded age of an employee, we use the number of years that we can observe a worker as being in employment each April, as far back as 1975, by linking ASHE to its predecessor, the New Earnings Survey Panel Dataset (NESPD) (Office for National Statistics, 2017), as another proxy for labour market experience.[7]

We define a *new hire* as an employee who joined their firm less than a year before the April reference period, based on the start date of the employment relationship reported by the employer. Table 1, columns (I) and (II), display descriptive statistics for the new hires in ASHE from 2005-2020, broken down by gender. On average, men are hired with higher wages and more years of labour market experience beforehand. Women are notably more likely to be hired by the public sector and to have their pay affected by a collective agreement than men. We also observe that women work, on average, fewer hours than men, highlighting the advantage of our data, which allows us to control for hours worked by deriving hourly wage measures.

For some firms and occupations, we only see either men or women being hired in a given year. The presence of such single-gender hiring firms and occupations poses an issue for examining their role in the gender hiring wage gap; we cannot observe the hiring wages that would be offered to women at all-male firms and occupations or to men at all-female firms and occupations. Therefore, for some of our analyses, we will limit attention to firms where we observe at least one worker of each gender being hired into the same 4-digit occupations in the same year. Since the gender wage gap among single-gender firms/occupations is relatively

[7]The NESPD does not contain firm identifiers, so we can only look within jobs and between co-workers from 2005 onward.

TABLE 1: Descriptive statistics for new hires (less than 12 months tenure)

	All ASHE hires		Dual-gender sample		Reduced sample	
	Mean (I)	St. dev. (II)	Mean (III)	St. dev. (IV)	Mean (V)	St. dev. (VI)
Hourly wage (2002 GBP)						
Men	9.27	8.78	7.41	5.90	8.57	6.39
Women	8.08	5.09	6.93	4.36	7.88	5.04
Basic wage (2002 GBP)						
Men	8.87	7.86	7.06	5.60	8.09	5.90
Women	7.84	4.84	6.64	4.07	7.52	4.73
Weekly hours						
Men	33.25	11.78	27.51	13.03	30.86	11.27
Women	27.29	12.46	24.03	12.70	27.48	11.59
Age (years)						
Men	32.71	12.01	28.54	11.18	31.80	11.50
Women	32.29	11.93	29.20	11.74	32.72	12.12
Years employed						
Men	5.74	7.17	3.94	5.74	7.08	7.17
Women	5.40	6.39	3.97	5.32	7.00	6.55
Public sector (%)						
Men	9.2		12.3		19.2	
Women	18.8		13.1		18.7	
Coll. agreement (%)						
Men	29.5		37.8		44.5	
Women	35.4		37.7		44.0	
Last job:						
Hourly wage (2002 GBP)						
Men					8.16	5.69
Women					7.45	4.65
Basic wage (2002 GBP)						
Men					7.74	5.18
Women					7.17	4.35
Tenure (years)						
Men					3.16	5.01
Women					3.18	4.57
Full-time (%)						
Men					65.1	
Women					48.5	
N men	162,535		39,593		9,824	
N women	174,481		44,775		11,204	

Notes: Author calculations using the ASHE (2005-2020) and the NESPD (1975-2016). 'Hourly wage' deflated to 2002 pound sterling using the UK Consumer Price Index for April. 'All ASHE hires' gives statistics for all observed new hires in the ASHE. 'Dual-gender sample', as defined in the text, gives statistics over the sample of new hires used for the main results in Table 3, columns (I)-(IV). 'Reduced sample', as defined in the text, gives statistics over the sample of new hires used in Table 3, column (V).

large, removing workers in these firms/occupations from the sample leads to substantially smaller gender gaps in the remaining dual-gender subsample than in the labour market as a whole, 12.8% versus 6.5%, respectively.[8] Appendix A provides further details about the samples, including the distributions of new hires over occupations, industries, and firm sizes.

3. Decomposing the Gender Wage Gap into Hires and Firm Stayers

To inform our subsequent discussion and analysis of the gender hiring wage gap within jobs, we first decompose the overall gender wage gap into its principal dynamic components, building on the work of Manning and Robinson (2004).

Suppose that we observe $i = 1, ..., N_0$ workers in year 0, and each worker had a log wage in that year of w_{0i}, with an average wage over all employees of $\overline{w}_0$. Define an indicator variable for each worker, θ_{1i}, which equals one if worker i is still employed one year later in the same firm and equals zero otherwise. We refer to workers with $\theta_{1i} = 1$ as *firm stayers*. We denote a firm-stayer's year-to-year log wage change by g_{1i}. *Hires* are workers with less than one year tenure with their current employer who were hired either from non-employment or directly from another employer. We denote the total number of hires in the following year (year 1) by H_1, and each hire has a log wage w^h_{1j}. Total employment in year 1 is thus $\sum_{i=1}^{N_0} \theta_i + H_1$, and the average employee wage in year 1 can be written as:

$$\overline{w}_1 = \frac{\sum_{i=1}^{N_0} \theta_{1i}(w_{0i} + g_{1i}) + \sum_{j=1}^{H_1} w^h_{1j}}{\sum_{i=1}^{N_0} \theta_{1i} + H_1} \,. \tag{1}$$

This equation splits overall average wages between those of hires and job stayers. Denoting the share of new hires in total employment by:

$$\alpha \equiv \frac{H_1}{\sum_{i=1}^{N_0} \theta_{1i} + H_1} \,,$$

[8] We calculate the gender pay gap as the difference between the average (mean) pay of men and women divided by the average pay of men, as per ONS official statistics. However, in most of what follows, we analyse differences between men's and women's log wages.

we can rewrite the year 1 average wage as:

$$\overline{w}_1 = \alpha \overline{w_1^h} + (1-\alpha)\left(\overline{w}_0 + \overline{g}_1 + \frac{\mathrm{Cov}(w_{0i}, \theta_{1i})}{\overline{\theta}_1}\right), \tag{2}$$

where the average log wage change $\overline{g}_1$ is computed only across firm stayers. Equation (2) shows that the average wage is a weighted average of the new hires' and firm stayers' average wages. The latter is equal to the sum of the firm stayers' average wages from the previous year, their average wage growth, and a covariance term, which captures the association between wages last year and the probability of an employee staying in the same firm till the next year. If this covariance term is positive, it implies that workers with higher wages are more likely to remain with their employer from one year to the next, such that the average wage among firm stayers was higher than the overall average wage in the previous year.

Using the dynamic Equation (2), we further examine the source of differences in firm stayers' past wages. We consider a steady state with a constant employment level, such that employment inflows must equal outflows:

$$\alpha = 1 - \overline{\theta}.$$

Assuming constant wages in steady state (which is not as restrictive as it might first appear because we deflate wages in our analysis), we can derive the steady-state average hourly wage:

$$\overline{w} = \overline{w^h} + \frac{1-\alpha}{\alpha}\left(\overline{g} + \frac{\mathrm{Cov}(w_i, \theta_i)}{1-\alpha}\right). \tag{3}$$

This expression shows that to understand the determinants of the average wage in a steady state, we must examine the average hiring wage and, adjusting for selection, the average change in the log wages of new hires. The level of hiring wages plays a central role in determining the overall average steady-state wage because, intuitively, every firm stayer was a new hire at some point. The role of hiring wages diminishes the longer the average job tenure, the higher the average wage growth, and the higher the positive wage selection of firm stayers.

By computing each term in Equations (2) and (3) separately by year and gender and subtracting the women's values from the men's in each year, we can characterise how the overall current gender wage gap and its implied steady-state level over time depend on the average gender differences in hiring wages and wage growth among firm stayers.

4. The Aggregate Importance of the Gender Hiring Wage Gap

In this section, we first discuss the results of applying the analytical decompositions described above for the current and implied steady-state gender gaps in average hourly wages and for each year between 2005 and 2020. We then assess the role of gender segregation across employers and occupations in accounting for the gender hiring wage gap.

Decomposition. Table 2 displays the results from decomposing the gender wage gap as per Equation (2), separately for men and women, for each year in 2005-2020, using 2004 wages from the New Earnings Survey Panel Dataset for the job stayers in 2004-05. To summarise, we present the overall averages of the year-by-year decomposition over the entire period 2005-2020 and for four-year sub-periods: 2005-08, 2009-12, 2013-2016, and 2017-2020 (Appendix Tables B1 and B2 list the complete annual estimates). The average gender gap in hourly wages is 15.6 log points from 2005 to 2020, with large movements over the sample period: it fell from 19.2 log points in 2005-08 to 12.6 log points in 2017-20. The decomposition results in Table 2 show that almost all of the latest period's gender wage gap, in 2017-20, can be attributed to the differences between last year's wages of male and female firm stayers; the differences between male and female firm stayers in the term $(1-\alpha)\overline{w_0}$ account for around 90% of the gender wage gap in all sub-periods. Once a wage gap emerges, it is highly persistent.

TABLE 2: Decomposition of the gender wage gap

	2005-2020		2005-2008		2009-2012		2013-2016		2017-2020	
	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
1. Share of new hires, α	0.172	0.174	0.171	0.175	0.147	0.148	0.176	0.176	0.193	0.198
2. Mean log hiring wage, $\overline{w_1^h}$	2.086	2.002	2.118	1.996	2.073	1.987	2.024	1.958	2.130	2.066
3. Mean log stayer wage, $\overline{w}_0$	2.340	2.179	2.374	2.177	2.371	2.199	2.291	2.145	2.324	2.195
4. Mean log wage change, $\overline{g}_1$	0.020	0.020	0.031	0.031	−0.001	0.001	0.025	0.023	0.026	0.027
5. Mean covariance term, Cov/$\overline{\theta}_1$	0.034	0.026	0.029	0.022	0.028	0.022	0.033	0.023	0.046	0.035
6. Mean log wage, $\overline{w}_1$	2.342	2.186	2.380	2.189	2.350	2.188	2.292	2.150	2.345	2.219
7. Gender hiring wage gap	0.084		0.122		0.086		0.066		0.064	
8. Current gender wage gap	0.156		0.192		0.162		0.142		0.126	
9. Steady-state gender wage gap	0.129		0.169		0.111		0.121		0.117	
10. Steady-state hiring wage gap share	0.651		0.722		0.775		0.545		0.547	
11. N firm-stayer, N_0	754,091	794,741	182,164	182,319	196,820	206,373	204,725	218,255	170,382	187,794
12. N new hires, H_1	156,037	167,291	37,455	38,653	33,726	35,342	43,633	46,544	41,223	46,752

Notes: Summary of decomposition results for the average log hourly wage in the current year following Equation (2). Row 1 shows the share of new hires in total employment. Row 2 shows the current average log hourly wage of new hires. Row 3 shows last year's average log hourly wage of firm stayers. Row 4 shows the average year-to-year change in the log hourly wages of firm stayers. Row 5 shows the average covariance term divided by the average proportion of firm stayers. Row 6 shows the current average log hourly wage. Row 7 shows the difference between the average log hourly hiring wages of men and women computed using the values in row 2. Row 8 shows the difference between the average log hourly wages of men and women computed using the values in row 6. Row 9 shows the implied steady-state log hourly wage gap, computed according to Equation (3). Row 10 shows the share of the log hiring wage gap in the steady-state log hourly wage gap, computed using the values in rows 7 and 9. Row 11 shows the number of firm stayers. Row 12 shows the number of new hires. Based on the ASHE (2005-2020) and New Earnings Survey Panel Dataset (2004). All statistics are unweighted sample averages. See Appendix Tables B1 and B2 for the annual time series of men and women, respectively.

Using Equation (3), we compute the implied steady-state gender wage gap and display the results in row 9 of Table 2. The steady-state gender wage gap is, on average, 12.9 log points and follows a clear pattern over our sample period: it was 16.9 log points in 2005-08 and fell substantially during the financial crisis to 11.1 log points, where it has remained approximately stable since. As can be shown analytically, the speed of convergence of the gender wage gap to its steady-state value is approximately proportional to its distance from $\overline{w}$. This may explain why the decline in the gender wage gap has slowed down from initially 2.9 log points between 2005-08 and 2009-12 to just 1.6 log points between 2013-16 and 2017-20: Given the relative constancy of the steady state since 2009-12, the gender wage gap has consistently approached this level, and so the speed of convergence has decreased.

What drives the steady-state gender wage gap? Although the differences between last year's wages of male and female firm stayers are sizeable, they are themselves the outcome of gender differences in the principal components of the steady-state wage gap. Of these components, gender differences in hiring rates, wage growth rates in the firm, and employee retention rates combined can only account for around one-third of the steady-state gender wage gap. By contrast, the average hiring wage gap over 2005-20 is around 8.4 log points, implying that around two-thirds of the steady-state wage gap originates from hiring wages (row 10 of Table 2).[9]

Segregation. To understand what can explain the gender hiring wage gap, we now analyse the differences in where men and women work across both firms and occupations. This analysis captures both selection and discrimination in terms of who gets hired by which firm and into which occupation. Differences between the firm stayers' covariance terms are also important for the gender wage gap. However, we lack the information in our payroll-based dataset to study these terms more closely, notably information on childbirth and complete labour market experience (e.g., Costa Dias, Joyce, and Parodi, 2020). For some evidence on these covariance terms, we refer the reader to Manning and Swaffield (2008), who could study

[9]The hiring wage gap is with 8.4 log points, or around 8.8%, smaller than the values in Table 1, column (I), imply. This is because the hiring wage distribution is right-skewed, particularly for men, and we use the natural logarithm to transform hiring wages in the decomposition and below estimations.

the personal and family characteristics in their household survey data since their analysis did not require employer identifiers.

To examine the contributions of observable worker characteristics, occupational segregation, firm segregation, and firm-occupation segregation to the gender hiring wage gap, we estimate the following regressions using least squares (with a slight abuse of notation):

$$\log(w_{ifot}) = \text{constant}_t + \gamma_t \text{ Female}_i + \text{ Firm}'_{ft}\phi_t + \text{ Occ}'_{ot}\omega_t + \text{x}'_{it}\beta_t + \varepsilon_{ifot} \;, \tag{4}$$

and

$$\log(w_{ifot}) = \text{constant}_t + \gamma_t \text{ Female}_i + \; (\text{Firm}_{ft} \times \text{Occ}_{ot})'\eta_t + \text{x}'_{it}\beta_t + \varepsilon_{ifot} \;, \tag{5}$$

where w_{ifot} is the hourly wage of worker i who is hired by firm f in occupation o in year t. 'Female' equals one if worker i is female and zero otherwise, and γ_t gives the 'unexplained' or 'residual' gender hiring wage gap each year. 'Firm' is a firm-specific wage effect for the worker's hiring employer f in year t. 'Occ' likewise gives a wage effect each year for occupation (3-digit or 4-digit levels), and x is a vector of worker characteristics that includes age and its square, with time-varying coefficient vector β. We estimate Equations (4) and (5) over all newly hired employees in the ASHE from 2005 to 2020, allowing all coefficients to change from one year to the next.

Figure 1A plots the differences in the annual averages of the coefficient estimates from Equation (4) using 3-digit occupation categories. For example, the first datapoint in 2005 of the dashed line labelled 'Firms' shows:

$$\mathbf{E}_i[\text{Firm}'_{ft}\widehat{\phi}_t \mid \text{Female}_i = 0,\; t = 2005] - \mathbf{E}_i[\text{Firm}'_{ft}\widehat{\phi}_t \mid \text{Female}_i = 1,\; t = 2005],$$

where $\mathbf{E}_i[\cdot]$ denotes the expected value across all workers. First, we see that the raw hiring wage gap declined from above twelve log points in 2005-08 to around six log points in 2017-20. The role of segregation of women into lower-paying occupations also declined over time, accounting for only slightly above one log point in 2017-20. The contribution of firm segregation to the overall hiring wage gap is approximately constant over the sample period at two log points. The included covariates do not contribute meaningfully to the hiring wage gap. Figure 1 also shows the estimated residual or unexplained part of the gender hiring wage gap, $\widehat{\gamma}_t$, which is the remainder after accounting for occupations, firms, and the covariates. According to Equation (4), the unexplained gap declined from six to four log points in 2010 and has been roughly stable since then.

Panel B of Figure 1 displays the results from estimating Equation (5), but here we analyse the maximum level of detail by using 4-digit occupation categories. While the contribution of segregation into firm-occupation cells has declined substantially initially, the share of the unexplained part of the raw gender hiring wage gap has been approximately stable, according to Equation (5). Since 2014, the raw gap in hiring wages has been around 6 log points, with gender segregation into firm-occupation cells explaining roughly 4 log points and the unexplained gap accounting for the remaining 2 log points, on average.

Taken together, our decomposition results in this section suggest that changes to the gender wage gap are mainly driven by the hiring wage gap. Moreover, the hiring wage gap and, hence, the steady-state wage gap have been approximately stable over the past decade, which may explain the slowdown in the narrowing of the overall gender wage gap. This motivates a deeper examination of the hiring wage gap, which is largely unaccounted for by differences in the firms and occupations where men and women are hired.

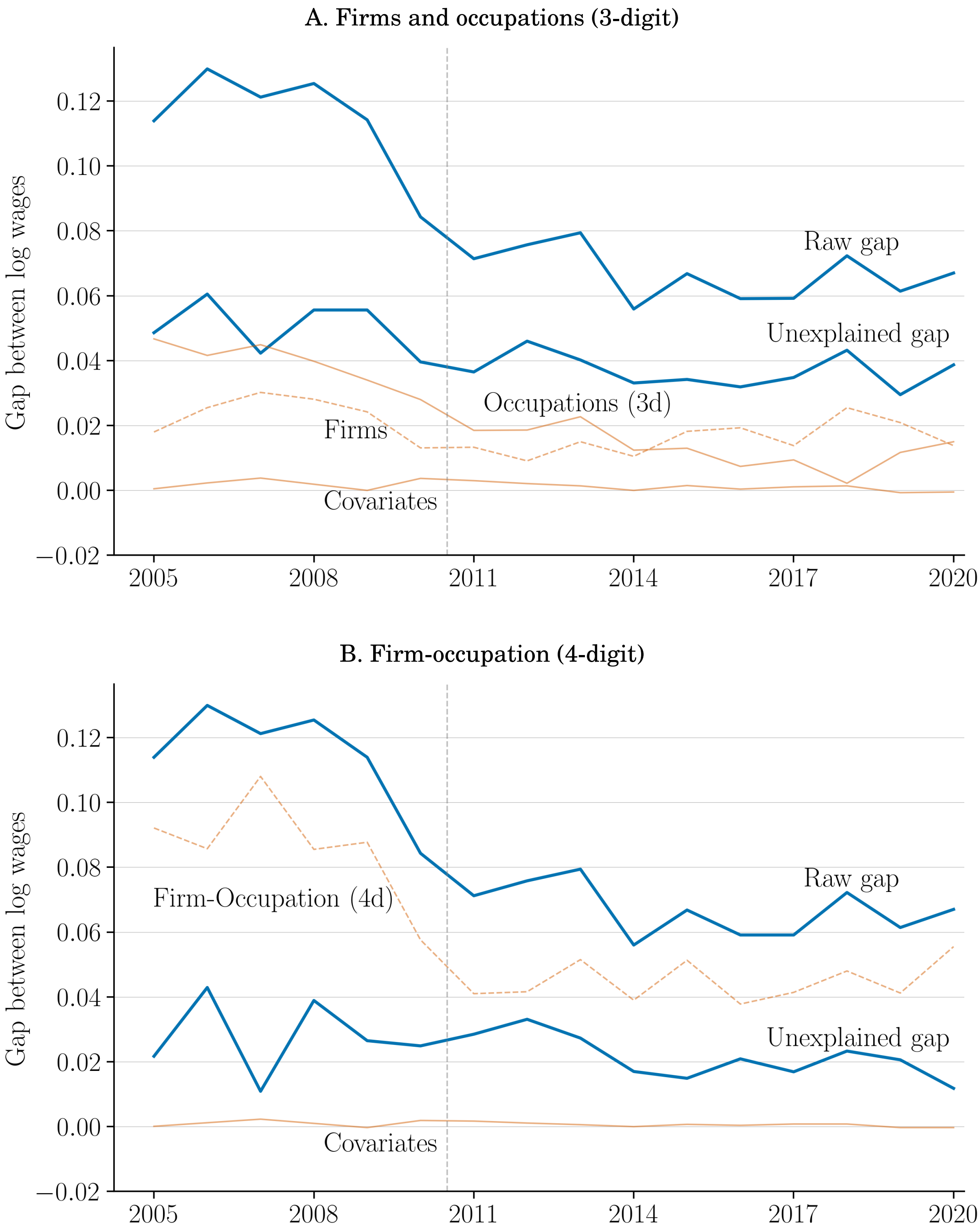

FIGURE 1: Contribution of firms, occupations, firm-occupation, and covariates to the gender hiring wage gap

Notes: Estimation results based on Equations (4) and (5), top and bottom panel, respectively. 'Raw gap' shows the difference between the average log hiring wages for men and women in a given year.
Panel A: 'Firms', 'Occupations (3d)', and 'Covariates' show sample averages of the estimates of the third, fourth, and fifth terms on the right side of Equation (4) for each year using 3-digit occupation categories, respectively; 'Unexplained gap' shows the estimates of $\widehat{\gamma}_t$ from Equation (4).
Panel B: 'Covariates' and 'Firm-Occupation (4d)' show sample averages of the estimates of $\hat{\beta}$ and $\hat{\eta}$ of Equation (5) for each year using 4-digit occupation categories, respectively; 'Unexplained gap' shows the estimates of $\widehat{\gamma}_t$ from Equation (5). Unweighted estimates based on the ASHE (2005-2020) and the New Earnings Survey Panel Dataset (2004). The vertical line indicates the change from SOC 2000 to SOC 2010. See Appendix Tables B3 (Panel A) and B4 (Panel B) for the underlying estimates.

5. The Hiring Wage Gap Within Jobs

In this section, we more comprehensively describe and quantify the aggregate significance of gender differences in hiring wages. We limit attention to firms that hire at least one worker of each gender into the same 4-digit occupation and the same year (hereafter referred to as a *job*) within the previous 12 months. This dual-gender sample of men and women, described in Table 1, columns (III) and (IV), includes just over one-quarter of the hires in the entire ASHE. Compared to all new hires, workers in the dual-gender sample have lower gross and basic hiring wages, are younger, are less experienced, and the women are less likely to be hired by the public sector. The gender hiring wage gap is also smaller in this subsample than in the entire ASHE (6.5% versus 12.8%), reflecting the omission of single-gender jobs, which, as discussed above, have larger gender differences in pay between them.

Next, we compute the difference between men's and women's average log wages within each job in the dual-gender sample. The light bars in Figure 2 show that there is substantial dispersion in the gender wage gaps among new hires. Only eight per cent of employees start jobs where the women's hiring wages are, on average, within half a log point of the men's hiring wages in the same year; the average employee in the sample is hired into a job with a hiring wage gap of 1.9 log points between men and women.

When instead looking at all the employees (not only new hires) in the same set of firms and years as the jobs in our dual-gender sample, without requiring that men and women work in the same occupations, the dark bars in Figure 2 show that the overall average gender wage gaps at the firm-level are generally much larger than hiring gender wage gaps within jobs at the same firms. This could be explained by factors which have been widely studied elsewhere but are beyond our focus on the hiring wage gap here (e.g., constraints that prevent women from working long hours to compete with men and thus progress in their careers; Cortés and Pan, 2019; Goldin, 2014). Nonetheless, in an even more heavily selected sample of employees who stay in the same job for up to two years after we observe them as a new hire alongside somebody of the opposite gender, we find no significant gender differences in year-to-year wage growth within jobs.

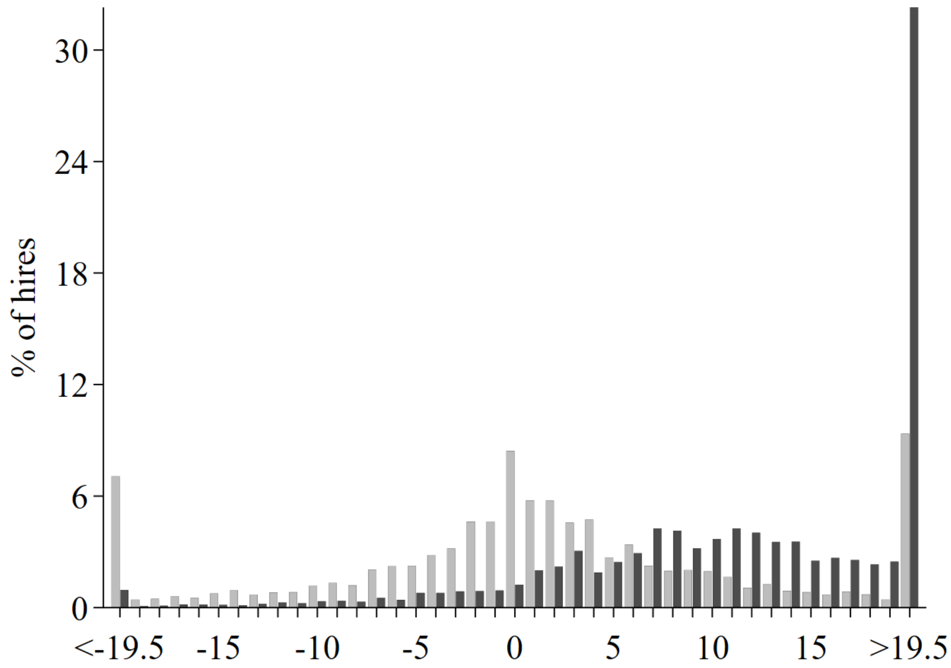

FIGURE 2: Distributions of the log hiring wage gap within jobs over new hires and the log wage gap across all other employees within the same firms

Notes: Based on the ASHE (2005-2020). The zero bar shows the range $[-0.5, 0.5]$. Bars to the right and left then go up and down in one log point increments. Light bars: Mean difference in log wages between men and women (male-female) who were hired in the same year and the same firm-occupation (mean = 1.9 and st. dev. = 19.0). Dark bars: Difference in log wages between all men and women in a firm-year that features in the hiring sample, not necessarily in the same occupation (mean = 15.2 and st. dev. = 14.5).

To more formally analyse the hiring wage gap, we estimate the following wage regression using least squares (again, somewhat abusing notation):

$$\log(w_{ifot}) = \text{constant} + \gamma \times \text{Female}_i + x'_{it}\beta + \lambda_{fot} + \varepsilon_{ifot} \ , \tag{6}$$

where, as before, w_{ifot} is the hourly wage of worker i hired into firm f and occupation o in year t. Female_i is an indicator that equals 1 for women and is 0 for men, γ estimates the unexplained or residual within job female wage penalty, x_{it} is a vector of covariates described below (e.g., worker's age), with associated coefficients in β. The variable λ_{fot} is a firm-year-occupation-fixed effect or *job*-fixed effect. The remaining unobserved wage variation is in the residual ε_{ifot}. We begin by pooling the years in our estimation sample, obtaining a single estimate of γ, before relaxing this later.

If the covariates x_{it} are omitted, then using our dual-gender sample yields identical coefficient estimates of γ as estimating Equation (6) using the sample of all new hires in the ASHE dataset that was described in the previous sections. To see this, note that we identify γ by exploiting the within-job variation of hiring wages by gender. This is only possible if we observe at least one newly hired worker of each gender in a firm-occupation-year cell. Additionally, when we control for job-level clustering, we also obtain the same standard errors. If covariates are included, estimates likely differ because their coefficient estimates are additionally based on the wages of new hires in jobs without both genders.

We prefer our approach, restricting the estimation to the dual-gender sample, because it offers two main advantages: First, it is more transparent about the number of observations actually used to estimate the coefficient of interest γ, and second, the estimated effects of covariates on hiring wages are based only on their impact in our dual-gender sample rather than for all new hires in Great Britain. This matters because very segregated jobs that do not hire both genders may remunerate observable characteristics differently from jobs in which men and women are commonly hired together.

Table 3 displays the results from estimating Equation (6) using different sets of fixed effects, and Appendix Figure C1 displays the estimates $\widehat{\gamma}$ by year. Column (I) shows that the gender hiring wage gap in the dual-gender sample is 4.6 log points. That is, women earn, on average, around 4.7% less per hour than men hired into the same job. In the previous section, we found that the raw gender hiring wage gap among all new hires is, on average, 8.4 log points (Table 2).

When we control for the average hiring wage within firm-years and 3-digit occupation-years (column II), the estimated unexplained wage gap is 2.1 log points, indicating that women were more likely to be hired by low-wage firms or occupations, or in years with lower average wages. Once we additionally control for 4-digit occupations within the same firm and year (λ_{fot}), the average hiring wage gap within jobs is 2.0 log points (column III) and stable since 2014 (Appendix Figure C1), consistent with our findings in the previous section (Figure 1, Panel B).

TABLE 3: Estimation results for the gender hiring wage gap within jobs

Coefficient	(I)	(II)	(III)	(IV)	(V)
1. Female ($\hat{\gamma}$)	-0.0455^{***}	-0.0211^{***}	-0.0200^{***}	-0.0262^{***}	-0.0355^{***}
	(0.0032)	(0.0017)	(0.0016)	(0.0016)	(0.0051)
2. Age				0.0058^{***}	0.0013^{***}
				(0.0002)	(0.0004)
3. Age×Female					-0.0010^{**}
					(0.0005)
4. Age^2 (00s)				-0.0245^{***}	-0.0119^{***}
				(0.0009)	(0.0023)
5. Age^2×Female (00s)					0.0073^{**}
					(0.0028)
6. Years employed				0.0034^{***}	0.0010
				(0.0004)	(0.0009)
7. Years employed×Female					−0.0008
					(0.0012)
8. (Years employed)^2 (00s)				-0.0083^{***}	−0.0100
				(0.0019)	(0.0043)
9. (Years employed)^2×Female (00s)					0.0087
					(0.0064)
10. log(weekly hours)				-0.0112^{***}	-0.0206^{***}
				(0.0024)	(0.0074)
11. log(weekly hours)×Female					−0.0019
					(0.0081)
12. Previous log(wage)					0.2165^{***}
					(0.0132)
13. Previous log(wage)×Female					-0.0277^{***}
					(0.0112)
14. Previous tenure					−0.0017
					(0.0006)
15. Previous tenure×Female					0.0013
					(0.0010)
16. Previous full-time					0.0109^{*}
					(0.0056)
17. Previous full-time×Female					0.0086
					(0.0074)
Constant	1.8865^{***}	1.8736^{***}	1.8730^{***}	1.8507^{***}	1.6368^{***}
Firm-Year FEs		✓			
Occupation-Year (3d) FEs		✓			
Firm-Year-Occupation (4d) FEs			✓	✓	✓
R^2	0.003	0.757	0.781	0.792	0.829
N firm-years/jobs		9,820	13,134	13,134	4,533
N hires	84,368	84,368	84,368	84,368	21,028
Equiv. ‘Female’ estimate ($\hat{\gamma}$) in the column (V) sample	-0.0594^{***}	-0.0312^{***}	-0.0305^{***}	-0.0350^{***}	

Notes: Estimation results based on Equation (6), the ASHE (2005-2020), and the NESPD (1975-2016). The sample contains jobs (firm-4-digit-occupation-year) in which at least one man and one woman joined the firm in the past year. Wages are deflated to 2002 pound sterling using the UK Consumer Price Index for April. ‘Age’ measures the age of a new hire in years. ‘Years employed’ measures the number of years we observe a new hire in any previous jobs in the ASHE and the NESPD since 1975. ‘Weekly hours’ are basic, i.e., excluding any overtime. ‘Previous log(wage)’ is the log wage in the previous job of a new hire in the last two years. ‘Previous tenure’ measures tenure in the previous job in years. ‘Previous full-time’ is an indicator that equals one if the previous job was a full-time position (≥30 hours) and 0 otherwise. We centre variables around their estimation sample averages before squaring or interacting. The final row shows the equivalent estimates of $\hat{\gamma}$ for the same model as the column but using only the sample of 21,028 employees in column (V), with full results in Appendix Table B5.

***,**,* indicate significance from zero at 1%, 5% and 10% levels, respectively, two-sided tests. Standard errors in parentheses are robust to Firm-Year-Occupation clusters.

In column (IV) of Table 3, we add controls for a new hire's labour market experience using two proxies: age and the number of years we can observe a worker being employed back as far as 1975, as well as squared values of those variables.[10] Hiring wages are an increasing and concave function of both these experience measures. We also control for a new hire's log basic weekly hours worked, i.e., excluding overtime, which has a small but significantly negative effect on the hiring wage within jobs. Adding these control variables in column (IV) results in an estimated hiring wage gap within jobs of 2.6 log points; over half of the gender hiring wage gap in the dual-gender sample is left unexplained.

The estimate of 2.6 log points is economically significant, translating into annual earnings of £374 (2002 pound sterling) for the average female new hire in our sample in the year of hiring.[11] Moreover, as we showed in the last section, around two-thirds of the steady-state wage gap can be accounted for by gender differences in hiring wages (Table 2). Our finding that half of the hiring wage gap is unexplained translates roughly into one-third of the steady-state wage gap, or 4.3 log points, being left unexplained after controlling for observable characteristics and detailed job-fixed effects.

For some jobs in the dual-gender sample, we observe at least one male and one female new hire who both had payroll records for a previous job in at least one of the past two years.[12] For this reduced subsample of new hires, we observe the most recent past wage, tenure, and full-time status in the previous job. Employees in this sample are, on average, somewhat older, are more likely to be hired into the public sector, have more previous years of work experience, and receive higher wages than in the dual-gender sample (Table 1, columns V and VI). The hiring wage gap is somewhat larger in this sample compared to the dual-gender sample, 8.1% versus 6.5%.

[10] The ASHE gives no information on a worker's education. However, we expect to account for most of the gender differences in education and their influence on wages by controlling for detailed occupations within the job fixed effects since Chevalier (2007) documents that there are no gender differences at education levels in the early career occupations of UK employees.

[11] 2002 pound sterling and using men's average hourly hiring wage £9.23 (Table 1), assuming the average annual hours worked in the UK of 1,538 (OECD, 2020): £9.23 × 1,538 × (exp(0.026) − 1).

[12] We do not consider using information from workers' past jobs that are further in the past to exclude individuals with long breaks from work, which would likely correlate with both gender and wages.

We add the additional controls to x_{it} and also interact them with Female$_i$ to test whether the controls have different effects on hiring wages for men and women. Column (V) of Table 3 shows the resulting estimates of Equation (6). The final row in Table 3 shows the equivalent estimates of the female wage penalty, $\widehat{\gamma}$, using the reduced sample of column (V) for the models in columns (I)-(IV). Tenure and full-time status in the previous job do not significantly affect a new hire's wage within a job. However, a new hire's previous wage has a statistically significant effect on their new hourly earnings compared with their fellow new hires, but significantly less so for women. The estimated elasticity of the hiring wage to the previous job's wage is 0.216 for men, compared with 0.188 for women. This finding is consistent with the notion that, compared with their male colleagues, women negotiate less often or less successfully and ask for lower wages (Roussille, 2024; Säve-Söderbergh, 2019).

5.1. Extensions and Discussion

Gender differences across the hiring wage distribution. We estimate the wage equation in column (IV) of Table 3 for the different quartiles of the job-level hiring wage distribution. This allows us to compare estimates from the lowest-paid quarter of jobs in the sample with the highest-paid quarter and examine whether the UK National Minimum Wage (NMW) impacts the hiring wage gap. The unexplained gender wage gap within jobs is statistically significant in each quartile of the hiring wage distribution, but the largest gap (4.7 log points) exists between men and women who are hired into jobs in the top quartile (Appendix Table B7). This may suggest that jobs with wages further away from the UK NMW exhibit larger hiring wage gaps. Figure C1 plots the female hiring wage penalty estimates, $\widehat{\gamma}$, for each year in the sample between 2005 and 2020 and for the models corresponding to columns (I), (III) and (IV) in Table 3. All three estimates of the hiring wage gap narrowed since 2005 but stagnated over the past five years.

Basic wages. We repeat all estimations in Table 3 using the *basic* hourly wage as the dependent variable, which excludes extra pay components such as incentive pay or shift premium pay (Appendix Table B6). The gender hiring wage gap in basic wages within jobs is slightly smaller at 2.2 log points. This result suggests that the non-basic components of pay explain only a small part of the overall hiring wage gap. We also find that basic hours worked have no significant effect on basic hourly hiring wages, and their small negative impact on hourly earnings is accounted for by the components of pay that do not vary with hours worked, e.g., meal and travel allowances.

Geography and plants. A potential concern for the validity of our results could be that men are systematically more likely to be hired in high-paying regions than women, for example, if a supermarket chain has multiple stores across regions. To investigate this, we include fixed effects for the workplace region in Equation (6) to control for around 150 British regions (e.g., inner London versus outer London). All our results are robust to these workplace-region fixed effects, suggesting that different hiring locations do not explain the gender hiring gap. For a subset of observations, we also have 'plant-identifiers'. Using this subset, we can compare the hiring wages of men and women hired into the same occupation by the same firm in the same year, *and into the same plant*. Our coefficient estimates are robust to this refinement, though the smaller sample size leads to larger standard errors. We, therefore, prefer to work with our original sample definition, focusing on hires by the same enterprise.

Professional jobs and collective agreements. To further explore the gender difference in the effect of the previous wage on the hiring wage, we estimate the equivalent regression as column (V) of Table 3 for sub-samples of jobs (Appendix Table B7). First, we approximate 'professional' jobs by those not in the retail, hospitality or catering industry and that are classified as managerial, professional or technical occupations.[13] We find a greater unexplained wage gap among these professional jobs (4.95 log points) than among the remaining 'non-professional' jobs (2.5 log points). The elasticity of a man's hiring wage to his previous wage among the former set of jobs is relatively small and just significant from zero at the 5% level, and there is no significant difference there for women. Second, we consider jobs separately by whether some collective pay agreement covers them.[14] We find that an employee's last wage significantly matters for the hiring wage regardless of whether a

[13]We use the ONS Standard Industrial Classification 2003 (G-H: Wholesale and retail, Hotels and restaurants) and the SOC 2000/2010 (1-3: Managers, directors and senior officials, Professional occupations, and Associate professional and technical occupations.

[14]The ASHE records whether an employee's pay is set with reference to an agreement affecting more than one worker, e.g., pay agreed by a trade union or a workers' committee. We classify this as a worker's pay being subject to a collective agreement.

collective agreement covers the job. However, a woman's previous wage matters significantly less than a man's in jobs not covered by a collective pay agreement. These findings might be explained by a loss of human capital, which is not transferable from the previous job to the new job. As Kambourov and Manovskii (2009) have shown, wages in the United States substantially rise with occupational tenure rather than with employer or industry tenure, indicating that human capital is mostly occupation-specific. Postel-Vinay and Sepahsalari (2023) found similar results for the United Kingdom in household survey data. Therefore, we examine whether occupational switchers drive our results: employees who switch occupations might not be able to use previously accumulated human capital optimally. We include an indicator variable for when the new job is in a different 3-digit (2-digit) occupation than the last job and find that the coefficient on this variable is negative and significant. This finding suggests that occupation switching indeed implies a hiring wage penalty. However, the coefficient of the gender dummy variable, γ, remains effectively unchanged. Additionally, the coefficient estimates of the last job's wage and the previous job's wage for women are also almost unchanged.

Non-wage amenities. One frequently suggested explanation for women's lower wage outcomes is that women systematically value non-wage amenities higher than men, such that compensating differentials lead to lower wage bargains (Morchio and Moser, 2024). For example, Bowlus (1997) shows that quit rates for personal reasons (e.g., family, pregnancy, health) differ significantly between men and women and can account for 20%-30% of the gender wage gap. Related, Manning (2003) documents how women are more constrained in their opportunities to change jobs than men and are less concerned with money. However, we control for two of the most cited non-wage amenities: occupation and hours worked (Card, Cardoso, and Kline, 2016). Another important non-wage amenity is commuting time. Le Barbanchon, Rathelot, and Roulet (2021) have shown that women prefer shorter commuting times more strongly than men. If caring responsibilities are primarily the responsibility of women, this can limit the time available for commuting to higher-paying job opportunities. Using detailed postcode data from the ASHE, Petrongolo and Ronchi (2020) find evidence consistent with the view that women are willing to trade off commuting time against wages in Britain: women experience less earnings gains from job mobility than men, but also do not see as large increases in commuting distance as men.[15]

6. Conclusion

In a large sample of jobs and representative payroll data from Great Britain, we decompose the overall gender wage gap in terms of pay progression within firms versus hiring wages, finding that the latter is the primary component; hiring wage differences account for more than two-thirds of where the average hourly gender wage gap is heading in the coming years if it continues converging to its steady state value. The segregation of men and women over different firms and occupations can, at most, explain 40% of the recent hiring wage gap in Great Britain. Where we observe men and women who are hired at approximately the same time into the same firm and specific occupation, we find a raw gender hiring wage gap of 4.6%. After controlling for job-year-specific wage effects, the estimated unexplained hiring wage gap is two per cent. Still, it increases to 2.6% after further controlling for new hires' age and proxies of previous labour market experience. We also find that a man's last wage affects the hiring wage in his new job positively and significantly more so than for a woman within the same job, but not so in professional jobs or those covered by a collective pay agreement.

The sample of jobs studied here, where we can see comparable hiring wages for men and women, is by construction not entirely representative of jobs in the British labour market where both men and women are hired together. Instead, our analysis over-represents large firms in the services sectors, low-wage work, and jobs with more equal shares of men and women (see Appendix A). However, this is the limit of the extent of gender pay inequality that can be uncovered at the point of hiring within large payroll datasets because they do not typically contain records on both hours worked and specific occupations, which is one advantage of our dataset. Even so, a dataset with much larger samples of workers within firms would allow us to distinguish between different birth cohorts and age groups of new hires within jobs. It would be interesting then to study how much the entry-level or

[15] According to Petrongolo and Ronchi (2020), the average gender gap in commuting distance is 36 log points for women in their 40s and 40 log points for women in their 50s. Across all ages, men commute 24.3 km and women 15.7 km on average.

early-years hiring wages of successive cohorts can explain the cohort-driven decline in the gender pay gap documented by Arellano-Bover et al. (2024).

In the UK, a law came into effect in April 2018 requiring all firms with 250 employees or more to publicly and annually report their own gender wage gap statistics. There is evidence that this law has already reduced gender pay inequality within firms (Blundell et al., Forthcoming).[16] The approximate one per cent population sample of the ASHE prevents us from exploiting this quasi-experimental variation to analyse the effect of the reporting law on hiring wage gaps within jobs. However, this is an important area for future research.

Our findings could be important for policymakers who have viewed public pay gap reporting by firms as a low-cost and effective intervention in several countries (e.g., Austria, Denmark, and the United Kingdom) without yet distinguishing the hiring margin. Our findings may justify extending legislation or guidance to ask firms to report on gender differences at the hiring margin.[17] Hiring wages are less confounded by other factors than realised wages, which include, for example, every aspect of career progression within the firm. As such, any gaps revealed are likely to be more closely associated with (Un)Equal Pay, highlighting whether employers consistently pay men and women the same for work of equal or at least very comparable value.

[16]Examples of other countries include Austria and Denmark, where firms must report gender pay gaps to their employees instead of publicly. For evaluations of how these policies have affected pay gaps within firms, see Böheim and Gust (2021) for Austria and Bennedsen et al. (2022) for Denmark.

[17]Frimmel et al. (2024) find that mandating firms to state the offered wages when posting vacancies has led to only a small reduction of the gender wage gap in Austria.

7. References

Arellano-Bover, Jaime, Nicola Bianchi, Salvatore Lattanzio, and Matteo Paradisi. 2024. "One Cohort at a Time: A New Perspective on the Declining Gender Pay Gap." NBER Working Paper 32612.

Barach, Moshe A., and John J. Horton. 2021. "How Do Employers Use Compensation History? Evidence from a Field Experiment." *Journal of Labor Economics*, 39(1): 193–218.

Barth, Erling, Sari P. Kerr, and Claudia Olivetti. 2021. "The dynamics of gender earnings differentials: Evidence from establishment data." *European Economic Review*, 134(5): 103713.

Bayard, Kimberley, Judith Hellerstein, David Neumark, and Kenneth Troske. 2003. "New Evidence on Sex Segregation and Sex Differences in Wages from Matched Employee-Employer Data." *Journal of Labor Economics*, 21(4): 887–922.

Bennedsen, Morten, Elena Simintzi, Margarita Tsoutsoura, and Daniel Wolfenzon. 2022. "Do Firms Respond to Gender Pay Gap Transparency?" *Journal of Finance*, 77(4): 2051–2091.

Bertrand, Marianne, Claudia Goldin, and Lawrence F. Katz. 2010. "Dynamics of the Gender Gap for Young Professionals in the Financial and Corporate Sectors." *American Economic Journal: Applied Economics*, 2(3): 228–255.

Biasi, Barabara, and Heather Sarsons. 2022. "Flexible Wages, Bargaining, and the Gender Gap." *Quarterly Journal of Economics*, 137(1): 215–266.

Blau, Francine D., and Lawrence M. Kahn. 2017. "The Gender Wage Gap: Extent, Trends, and Explanations." *Journal of Economic Literature*, 55(3): 789–865.

Blundell, Jack, Emma Duchini, Ştefania Simion, and Arthur Turrell. Forthcoming. "Pay Transparency and Gender Equality." *American Economic Journal: Economic Policy*.

Böheim, René, and Sarah Gust. 2021. "The Austrian pay transparency law and the gender wage gap." Johannes Kepler University Linz Working Paper No. 2105.

Bowlus, Audra J. 1997. "A Search Interpretation of Male-Female Wage Differentials." *Journal of Labor Economics*, 15(4): 625–657.

Bronson, Mary A., and Peter S. Thoursie. 2021. "The Wage Growth and Within-Firm Mobility of Men and Women: New Evidence and Theory." Georgetown University Manuscript.

Card, David, Ana R. Cardoso, and Patrick Kline. 2016. "Bargaining, Sorting, and the Gender Wage Gap: Quantifying the Impact of Firms on the Relative Pay of Women." *Quarterly Journal of Economics*, 131(2): 633–686.

Cardoso, Ana R., Paulo Guimarães, and Pedro Portugal. 2016. "What drives the gender wage gap? A look at the role of firm and job-title heterogeneity." *Oxford Economic Papers*, 68(2): 506–524.

Chevalier, Arnaud. 2007. "Education, Occupation and Career Expectations: Determinants of the Gender Pay Gap for UK Graduates." *Oxford Bulletin of Economics and Statistics*, 69(6): 819–842.

Cortés, Patricia, and Jessica Pan. 2019. "When Time Binds: Substitutes for Household Production, Returns to Working Long Hours, and the Skilled Gender Wage Gap." *Journal of Labor Economics*, 37(2): 351–398.

Costa Dias, Monica, Robert Joyce, and Francesca Parodi. 2020. "The gender pay gap in the UK: children and experience in work." *Oxford Review of Economic Policy*, 36(4): 855–881.

Del Bono, Emilia, and Daniela Vuri. 2011. "Job mobility and the gender wage gap in Italy." *Labour Economics*, 18(1): 130–142.

Exley, Christine L., Muriel Niederle, and Lise Vesterlund. 2020. "Knowing When to Ask: The Cost of Leaning In." *Journal of Political Economy*, 128(3): 816–854.

Fortin, Nicole M., Brian Bell, and Michael Böhm. 2017. "Top earnings inequality and the gender pay gap: Canada, Sweden, and the United Kingdom." *Labour Economics*, 47: 107–123.

Frimmel, Wolfgang, Bernhard Schmidpeter, Rene Wiesinger, and Rudolf Winter-Ebmer. 2024. "External Pay Transparency and the Gender Wage Gap." Rockwool Foundation Berlin - CReAM Discussion Paper Series, No. 07/24.

Goldin, Claudia. 2014. "A Grand Gender Convergence: Its Last Chapter." *American Economic Review*, 104(4): 1091–1119.

Groshen, Erica L. 1991. "The Structure of the Female/Male Wage Differential: Is It Who You Are, What You Do, or Where You Work?" *Journal of Human Resources*, 26(3): 457–472.

He, Haoran, David Neumark, and Qian Weng. 2021. "Do Workers Value Flexible Jobs? A Field Experiment." *Journal of Labor Economics*, 39(3): 709–738.

Heinze, Anja, and Elke Wolf. 2010. "The intra-firm gender wage gap: a new view on wage differentials based on linked employer–employee data." *Journal of Population Economics*, 23(3): 851–879.

Jewell, Sarah L., Giovanni Razzu, and Carl Singleton. 2020. "Who Works for Whom and the UK Gender Pay Gap." *British Journal of Industrial Relations*, 58(1): 50–81.

Jones, Melanie, and Ezgi Kaya. 2023. "The UK gender pay gap: Does firm size matter?" *Economica*, 90(359): 937–952.

Kambourov, Gueorgui, and Iourii Manovskii. 2009. "Occupational Specificity of Human Capital." *International Economic Review*, 50(1): 63–115.

Kleven, Henrik, Camille Landais, and Jakob Egholt Søgaard. 2019. "Children and Gender Inequality: Evidence from Denmark." *American Economic Journal: Applied Economics*, 11(4): 181–209.

Kunze, Agnes. 2018. "The Gender Wage Gap in Developed Countries." In *Handbook on Women and the Economy*. Eds. Averett, S. L. and Argys, L. M. and Hoffman, S. D.. Oxford University Press.

Le Barbanchon, Thomas, Roland Rathelot, and Alexandra Roulet. 2021. "Gender Differences in Job Search: Trading off Commute against Wage." *Quarterly Journal of Economics*, 136(1): 381–426.

Macpherson, David A., and Barry T. Hirsch. 1995. "Wages and Gender Composition: Why do Women's Jobs Pay Less?" *Journal of Labor Economics*, 13(3): 426–471.

Manning, Alan. 2003. *Monopsony in Motion: Imperfect Competition in Labor Markets*. Princeton University Press, Princeton.

Manning, Alan, and Helen Robinson. 2004. "Something in the Way She Moves: A Fresh Look at an Old Gap." *Oxford Economic Papers*, 56(2): 169–188.

Manning, Alan, and Joanna Swaffield. 2008. "The Gender Gap in Early-Career Wage Growth." *Economic Journal*, 118(530): 983–1024.

Mas, Alexandre, and Amanda Pallais. 2017. "Valuing Alternative Work Arrangements." *American Economic Review*, 107(12): 3722–3759.

Morchio, Iacopo, and Christian Moser. 2024. "The Gender Pay Gap: Micro Sources and Macro Consequences." NBER Working Paper 32408.

Mumford, Karen, and Peter N. Smith. 2009. "What Determines the Part-Time and Gender Earnings Gaps in Britain: Evidence from the Workplace." *Oxford Economic Papers*, 61: i56–i75.

Nickell, Stephen, and Glenda Quintini. 2003. "Nominal Wage Rigidity and the Rate of Inflation." *Economic Journal*, 113(490): 762–781.

OECD. 2020. *OECD Employment Outlook 2020: Worker Security and the COVID-19 Crisis.* OECD Publishing, Paris.

Office for National Statistics. 2017. "New Earnings Survey Panel Dataset, 1975-2016: Secure Access. [data collection]." 7th Edition. UK Data Service. SN: 6706, http://doi.org/10.5255/UKDA-SN-6706-7.

Office for National Statistics. 2024. "Annual Survey of Hours and Earnings, 1997-2023: Secure Access. [data collection]." 25th Edition. UK Data Service. SN: 6689, http://doi.org/10.5255/UKDA-SN-6689-24.

Olivetti, Claudia, and Barbara Petrongolo. 2016. "The Evolution of Gender Gaps in Industrialized Countries." *Annual Review of Economics*, 8: 405–434.

Petrongolo, Barbara, and Maddalena Ronchi. 2020. "Gender gaps and the structure of local labor markets." *Labour Economics*, 64: 101819.

Postel-Vinay, Fabien, and Alireza Sepahsalari. 2023. "Labour Mobility and Earnings in the UK, 1992-2017." *Economic Journal*, 133(656): 3071–3098.

Roussille, Nina. 2024. "The Role of the Ask Gap in Gender Pay Inequality." *Quarterly Journal of Economics*, 139(3): 1557–1610.

Säve-Söderbergh, Jenny. 2019. "Gender gaps in salary negotiations: Salary requests and starting salaries in the field." *Journal of Economic Behavior and Organization*, 161: 35–51.

Sin, Isabelle, Steven Stillman, and Richard Fabling. 2022. "What Drives the Gender Wage Gap? Examining the Roles of Sorting, Productivity Differences, Bargaining and Discrimination." *Review of Economics and Statistics*, 104(4): 636–651.

Sorkin, Isaac. 2017. "The Role of Firms in Gender Earnings Inequality: Evidence from the United States." *American Economic Review: Papers & Proceedings*, 107(5): 384–387.

Unequal Hiring Wages and their Impact on the Gender Pay Gap

Online Appendix

Tho Pham Daniel Schaefer Carl Singleton†

Appendix A. Further Description of the Data

In this Appendix, we provide more details on the underlying samples of employees and jobs used in the analysis.

Table A1 shows the distribution of the number of employee observations in ASHE per job (firm-occupation-year) in the dual-gender and the reduced samples. Almost a third of the newly hired workers in the main analysis are in jobs where 2-5 other employees were hired in the same year and observed in the ASHE. A further 29% were hired into jobs with 6-20 new hires in the ASHE. Large jobs with more than 50 new hires in the ASHE account for 18% of the dual-gender sample. The reduced sample distribution, shown in the last column of Table A1, contains relatively more observations with small numbers of colleagues also being hired in the same year and observed within the ASHE (with a previous job).

The industry distribution of our dual-gender sample is displayed in Table A2. Industries classified as manufacturing (A-F) account for only a small share of the new hires because these jobs tend to be stable, so turnover is low, and also because the share of female hires is low in these industries, such that we often do not observe a male and female hires in the ASHE. Just over half of the new hires studied in the main text were in the wholesale and retail, and hotels and restaurants industry sectors.

The firm size distributions of new hires in the samples are shown in Table A3. Large firms with more than 1,000 employees account for almost 95% of the new hires studied in the main text. Large firms hire more workers, and so we are more likely to observe a female and a male hire in the same job in a given year within the overall ASHE sample of employees in Great Britain. Once we require to also observe the previous wage of the new hires from the past two years in the ASHE, the sample becomes even more dominated by large firms, as shown in the last column.

Table A4 displays the 20 most common occupations in the sample of new hires across all firms and occupations in the ASHE from 2011 to 2020 (the distribution for the years 2004-2010, when the previous occupational classification SOC 2000 was used, looks very similar). We observe 214,284 new hires in those 20 occupations, which represents 71% of all hires. The occupations 'Nursing and Midwifery', 'Secretarial and Related', and 'Childcare and Related Personal Services' have the highest shares of female hires at 86.8%, 86.7%, and 86.5%, respectively. The hiring wages in occupations with a majority of female hires tend to be relatively low, with notable exceptions in the occupations 'Nursing and Midwifery', 'Health Professionals', and 'Teaching and Educational Professionals'.

† carl.singleton@stir.ac.uk; corresponding author. This work is based on the Annual Survey of Hours and Earnings Dataset and New Earnings Survey Panel Dataset (Crown copyright 2024), having been funded, collected, and deposited by the Office for National Statistics (ONS) under secure access conditions with the UK Data Service (SN:6689 and SN:6706). Neither the ONS nor the Data Service bear any responsibility for the analysis and discussion of the results in this paper.

Related, Table A5 displays the 20 most common occupations in the dual-gender hiring sample where at least one man and woman were hired into the same firm-occupation-year from 2011 to 2020. Here, the 20 most common occupations represent 88% of all hires in the sample. By construction, the shares of male and female hires are more balanced because some firm-occupation-year cells that only included males or females are excluded from this sample.

TABLE A1: Distribution of sample new hires according to the number of hires per job (firm-4-digit-occupation-year) in the sample

Hires per job	Dual-gender sample	Reduced sample
2-5	0.327	0.462
6-20	0.290	0.386
21-50	0.204	0.125
50+	0.179	0.027

Notes: See Table 1 in the main text.

TABLE A2: Distribution of sample new hires over industry sectors

Industry Code	All ASHE hires	Dual-gender sample	Reduced sample
A-F	0.142	0.020	0.022
G-H	0.223	0.505	0.407
M-N	0.255	0.132	0.151
I-L, O	0.379	0.343	0.420

Notes: See Table 1 in the main text. Uses the Office for National Statistics Standard Industrial Classification 2003: A. Agriculture, hunting and forestry, B. Fishing, C. Mining and quarrying, D. Manufacturing, E. Utilities, F. Construction, G. Wholesale and retail, H. Hotels and restaurants, I. Transport and telecommunication, J. Financial intermediation, K. Real estate, business services, L. Public admin. and defence, social security, M. Education, N. Health and social work, O. Other community and social services.

TABLE A3: Distribution of sample new hires over firm (enterprise) sizes

Firm size (N employees)	ALL ASHE hires	Dual-gender sample	Reduced sample
<249	0.535	0.022	0.016
250-999	0.080	0.030	0.017
1,000-9,999	0.275	0.292	0.243
9,999+	0.110	0.656	0.724

Notes: See Table 1 in the main text.

TABLE A4: Distribution of new hires - All ASHE hires

SOC 2010	Description	Female share	Hiring wage (£)	*N*
711	Sales Assistants and Retail Cashiers	0.602	5.87	21,463
927	Other Elementary Services	0.569	5.45	16,724
614	Caring Personal Services	0.808	6.51	13,634
415	Other Administrative	0.700	7.49	12,666
926	Elementary Storage	0.202	6.16	8,839
923	Elementary Cleaning	0.655	5.73	8,466
354	Sales, Marketing and Related Assoc. Prof.	0.464	10.85	7,763
231	Teaching and Educational Prof.	0.681	12.77	7,523
721	Customer Services	0.570	6.39	7,031
821	Road Transport Drivers	0.048	6.92	6,029
612	Childcare and Related Personal Services	0.865	6.33	5,621
421	Secretarial and Related	0.867	6.83	5,481
412	Administrative Occupations: Finance	0.655	7.74	5,420
223	Nursing and Midwifery	0.868	10.95	4,012
242	Business, Research and Admin. Prof.	0.433	13.11	3,974
221	Health Professionals	0.575	14.94	3,912
913	Elementary Process Plant	0.280	5.92	3,669
543	Food Preparatory and Hospitality Trades	0.266	6.21	3,602
213	IT and Telecomm. Prof.	0.199	13.02	3,530
413	Administrative Occupations: Records	0.578	7.17	3,239

Notes: Distribution of new hires from 2011 to 2020 into the 20 most common occupation categories according to SOC 2010, representing 71% of new hires in the entire ASHE. 'Hiring wage' deflated to 2002 values using the Consumer Price Index.

TABLE A5: Distribution of new hires - Dual-gender sample

SOC 2010	Description	Female share	Hiring wage (£)	*N*
711	Sales Assistants and Retail Cashiers	0.585	5.55	15,081
927	Other Elementary Services	0.542	5.00	7,568
926	Elementary Storage	0.295	6.09	3,569
721	Customer Services	0.523	6.01	3,339
415	Other Administrative	0.533	7.23	2,987
614	Caring Personal Services	0.686	6.31	2,743
923	Elementary Cleaning	0.602	5.62	2,657
221	Health Professionals	0.508	15.85	1,463
231	Teaching and Educational Prof.	0.578	12.45	1,313
412	Administrative Occupations: Finance	0.534	7.15	1,143
223	Nursing and Midwifery	0.709	10.81	950
913	Elementary Process Plant	0.399	5.71	928
921	Elementary Administrative	0.352	6.76	731
411	Administrative Occupations: Government	0.495	7.88	685
612	Childcare and Related Personal Services	0.630	6.38	614
925	Elementary Sales	0.410	5.95	517
543	Food Preparatory and Hospitality Trades	0.335	6.02	510
354	Sales, Marketing and Related Assoc. Prof.	0.527	8.61	499
621	Leisure and Travel Services	0.519	5.99	495
242	Business, Research and Admin. Prof.	0.487	13.16	489

Notes: Distribution of new hires from 2011 to 2020 into the 20 most common occupation categories according to SOC 2010, representing 88% of new hires in the dual-gender hiring sample (at least one man and woman hired into the same firm-occupation-year). 'Hiring wage' deflated to 2002 values using the Consumer Price Index.

Appendix B. Additional Tables

TABLE B1: Decomposition results by year - Men

Year	$\overline{w}_0$ (I)	$\overline{g}_1$ (II)	Cov/$\overline{\theta}_1$ (III)	α (VI)	$\overline{w^h}_1$ (V)	$\overline{w}_1$ (VI)
2005	2.360	0.046	0.018	0.830	2.098	2.369
2006	2.369	0.032	0.028	0.837	2.127	2.380
2007	2.380	0.024	0.036	0.829	2.127	2.386
2008	2.386	0.023	0.034	0.821	2.122	2.385
2009	2.386	0.016	0.042	0.825	2.136	2.391
2010	2.390	−0.012	0.032	0.882	2.070	2.371
2011	2.371	−0.001	0.016	0.854	2.052	2.337
2012	2.337	−0.008	0.021	0.850	2.035	2.303
2013	2.303	0.005	0.031	0.852	2.025	2.292
2014	2.293	0.016	0.032	0.824	1.997	2.280
2015	2.280	0.041	0.032	0.810	2.019	2.290
2016	2.290	0.038	0.038	0.811	2.054	2.307
2017	2.307	0.040	0.039	0.807	2.093	2.329
2018	2.329	0.017	0.032	0.799	2.111	2.325
2019	2.325	0.026	0.039	0.797	2.120	2.335
2020	2.335	0.023	0.075	0.826	2.197	2.392

Notes: Annual decomposition results for men's average log hourly wage in the current year. Column (I) shows last year's average log hourly wage of firm stayers. Column (II) shows the average year-to-year change in the log hourly wages of firm stayers. Column (III) shows the average covariance term divided by the average proportion of firm stayers. Column (IV) shows the share of new hires in total employment. Column (V) shows the current average log hourly wage of new hires. Column (VI) shows the current average log hourly wage. Based on the ASHE (2005-2020) and New Earnings Survey Panel Dataset (2004).

TABLE B2: Decomposition results by year - Women

Year	$\overline{w}_0$ (I)	$\overline{g}_1$ (II)	Cov/$\overline{\theta}_1$ (III)	$1-\alpha$ (VI)	$\overline{w^h}_1$ (V)	$\overline{w}_1$ (VI)
2005	2.150	0.049	0.017	0.818	1.984	2.174
2006	2.174	0.028	0.024	0.833	1.997	2.188
2007	2.188	0.025	0.023	0.826	2.006	2.195
2008	2.195	0.021	0.024	0.823	1.997	2.197
2009	2.197	0.029	0.030	0.813	2.021	2.212
2010	2.212	−0.008	0.030	0.880	1.985	2.205
2011	2.205	−0.003	0.013	0.862	1.981	2.183
2012	2.182	−0.013	0.015	0.854	1.960	2.152
2013	2.152	0.004	0.025	0.850	1.945	2.145
2014	2.145	0.010	0.020	0.826	1.941	2.134
2015	2.134	0.037	0.022	0.810	1.952	2.147
2016	2.147	0.041	0.026	0.813	1.995	2.174
2017	2.174	0.036	0.027	0.808	2.034	2.198
2018	2.198	0.012	0.026	0.794	2.039	2.195
2019	2.195	0.032	0.029	0.787	2.059	2.213
2020	2.213	0.029	0.060	0.821	2.130	2.271

Notes: Annual decomposition results for women's average log hourly wage in the current year. See notes to Appendix Table B1.

TABLE B3: Regression estimates: Contribution of firm and occupation (3-digit) segregation to the gender hiring wage gap

Year	Raw gap	Unexplained gap	Covariates	Firms	Occupations (3d)
2005	0.1139	0.0486	0.0005	0.0180	0.0467
2006	0.1299	0.0605	0.0023	0.0255	0.0416
2007	0.1212	0.0423	0.0038	0.0302	0.0449
2008	0.1254	0.0556	0.0019	0.0281	0.0398
2009	0.1139	0.0556	0.0000	0.0242	0.0340
2010	0.0843	0.0396	0.0037	0.0131	0.0280
2011	0.0713	0.0365	0.0030	0.0133	0.0185
2012	0.0758	0.0460	0.0021	0.0091	0.0186
2013	0.0794	0.0402	0.0014	0.0150	0.0227
2014	0.0560	0.0331	0.0000	0.0105	0.0124
2015	0.0668	0.0342	0.0015	0.0182	0.0130
2016	0.0591	0.0319	0.0004	0.0193	0.0074
2017	0.0591	0.0348	0.0011	0.0138	0.0094
2018	0.0722	0.0432	0.0014	0.0255	0.0022
2019	0.0614	0.0295	−0.0007	0.0209	0.0117
2020	0.0670	0.0387	−0.0005	0.0138	0.0150

Notes: Estimation results for Equation (4). Based on the ASHE (2005-2020). See Figure 1 in the main text for details.

TABLE B4: Regression estimates: Contribution of firm-occupation (4-digit) segregation to the gender hiring wage gap by year

Year	Raw gap	Unexplained gap	Covariates	Firm-Occupation (4d)
2005	0.1139	0.0217	0.0001	0.0921
2006	0.1299	0.0429	0.0012	0.0857
2007	0.1212	0.0109	0.0023	0.1080
2008	0.1254	0.0389	0.0010	0.0855
2009	0.1139	0.0265	−0.0003	0.0877
2010	0.0843	0.0249	0.0019	0.0576
2011	0.0713	0.0285	0.0017	0.0410
2012	0.0758	0.0331	0.0011	0.0416
2013	0.0794	0.0273	0.0006	0.0515
2014	0.0560	0.0170	0.0000	0.0390
2015	0.0668	0.0149	0.0007	0.0513
2016	0.0591	0.0209	0.0004	0.0378
2017	0.0591	0.0169	0.0008	0.0414
2018	0.0722	0.0233	0.0008	0.0480
2019	0.0614	0.0206	−0.0003	0.0412
2020	0.0670	0.0118	−0.0003	0.0555

Notes: Estimation results for Equation (5). Based on the ASHE (2005-2020). See Figure 1 in the main text for details.

TABLE B5: Estimation results for the gender hiring wage gap within jobs, using the reduced sample from column (V) of Table 3

Coefficient	(I)	(II)	(III)	(IV)
1. Female ($\hat{\gamma}$)	−0.0594***	−0.0312***	−0.0305***	−0.0350***
	(0.0054)	(0.0036)	(0.0033)	(0.0033)
2. Age				0.0032***
				(0.0003)
3. Age^2 (00s)				−0.0171***
				(0.0015)
4. Years employed				0.0026***
				(0.0006)
5. (Years employed)^2 (00s)				−0.0087***
				(0.0032)
6. log(weekly hours)				−0.0197***
				(0.0059)
Constant	2.0168***	1.9990***	2.0013***	2.0232***
Firm-Year FEs		✓		
Occupation-Year (3d) FEs		✓		
Firm-Year-Occupation (4d) FEs			✓	✓
R^2	0.005	0.793	0.809	0.814
N firm-years/jobs		3,641	4,547	4,547
N hires	21,028	21,028	21,028	21,028
Equiv. 'Female' estimate ($\hat{\gamma}$) in Table 3	−0.0455***	−0.0211***	−0.0200***	−0.0262***

Notes: See Table 3 in the main text.
***,**,* indicate significance from zero at 1%, 5% and 10% levels, respectively, two-sided tests. Standard errors in parentheses are robust to Firm-Year-Occupation clusters.

TABLE B6: Estimation results for the gender hiring wage gap within jobs, using basic wages per hour instead of earnings per hour, excluding overtime, as dependent variable

Coefficient	(I)	(II)	(III)	(IV)
1. Female ($\hat{\gamma}$)	-0.0394^{***}	-0.0174^{***}	-0.0165^{***}	-0.0220^{***}
	(0.0030)	(0.0016)	(0.0015)	(0.0015)
2. Age				0.0057^{***}
				(0.0002)
3. Age^2 (00s)				-0.0228^{***}
				(0.0009)
4. Years employed				0.0035^{***}
				(0.0004)
5. (Years employed)^2 (00s)				-0.0087^{***}
				(0.0018)
6. log(weekly hours)				-0.0028
				(0.0022)
Constant	1.8456^{***}	1.8339^{***}	1.8334^{***}	1.7852^{***}
Firm-Year FEs		✓		
Occupation-Year (3d) FEs		✓		
Firm-Year-Occupation (4d) FEs			✓	✓
R^2	0.003	0.769	0.794	0.805
N firm-years/jobs		9,820	13,134	13,134
N hires	84,368	84,368	84,368	84,368

Notes: See Table 3 in the main text, dependent variable is the basic wage per hour.
***,**,* indicate significance from zero at 1%, 5% and 10% levels, respectively, two-sided tests. Standard errors in parentheses are robust to Firm-Year-Occupation clusters.

TABLE B7: Estimation results for the gender hiring wage gap within jobs across quartiles of the hiring wage distribution

Coefficient	Quartile I	Quartile II	Quartile III	Quartile IV
1. Female ($\widehat{\gamma}$)	-0.0165^{***}	-0.0160^{***}	-0.0182^{***}	-0.0468^{***}
	(0.0023)	(0.0023)	(0.0028)	(0.0045)
2. Age	0.0125^{***}	0.0032^{***}	0.0023^{***}	0.0074^{***}
	(0.0005)	(0.0002)	(0.0002)	(0.0005)
3. Age^2 (000s)	-0.0423^{***}	-0.0153^{***}	-0.0123^{***}	-0.0310^{***}
	(0.0018)	(0.0011)	(0.0012)	(0.0028)
4. Years employed	0.0030^{***}	0.0020^{***}	0.0022^{***}	0.0061^{***}
	(0.0007)	(0.0005)	(0.0006)	(0.0009)
5. (Years employed)^2 (000s)	-0.0056^{*}	-0.0079^{***}	-0.0058^{**}	-0.0181^{***}
	(0.0033)	(0.0024)	(0.0027)	(0.0049)
6. ln(weekly hours)	0.0138^{***}	0.0100^{***}	-0.0219^{***}	-0.1046^{***}
	(0.0030)	(0.0029)	(0.0050)	(0.0103)
Constant	1.4302^{***}	1.6596^{***}	1.9115^{***}	2.6009^{***}
Firm-Year-Occupation FEs	✓	✓	✓	✓
R^2	0.4011	0.1107	0.0971	0.6878
N jobs	2,634	2,687	2,810	5,003
N hires	21,095	21,113	21,070	21,090

Notes: First, the average hiring wage within each Firm-Year-Occupation is computed before the jobs are ranked into quartiles (over new hires). 'Quartile' column headers indicate for which quartile Equation (4) was estimated. ***,**,* indicate significance from zero at 1%, 5% and 10% levels, respectively, two-sided tests. Standard errors in parentheses are robust to Firm-Year-Occupation clusters.

TABLE B8: Estimates of the gender hiring wage gap by year

	(I)		(III)		(IV)			
Year	Coeff.	s. e.	Coeff.	s. e.	Coeff.	s. e.	N jobs	N hires
2005	−0.066	0.011	−0.018	0.006	−0.029	0.006	805	5,702
2006	−0.084	0.011	−0.035	0.006	−0.041	0.006	791	5,361
2007	−0.043	0.013	−0.006	0.006	−0.014	0.006	753	4,866
2008	−0.057	0.012	−0.032	0.007	−0.041	0.007	693	4,850
2009	−0.051	0.012	−0.022	0.006	−0.028	0.006	796	5,004
2010	−0.043	0.012	−0.024	0.007	−0.028	0.007	646	3,958
2011	−0.053	0.012	−0.029	0.007	−0.033	0.007	809	4,866
2012	−0.054	0.012	−0.030	0.006	−0.033	0.006	788	4,952
2013	−0.041	0.011	−0.023	0.006	−0.028	0.006	774	4,955
2014	−0.062	0.010	−0.020	0.005	−0.023	0.005	963	5,852
2015	−0.029	0.009	−0.013	0.005	−0.017	0.005	985	6,571
2016	−0.034	0.009	−0.016	0.005	−0.021	0.005	958	6,187
2017	−0.021	0.009	−0.012	0.006	−0.018	0.006	944	6,184
2018	−0.036	0.010	−0.015	0.006	−0.024	0.006	940	5,477
2019	−0.039	0.009	−0.015	0.005	−0.022	0.005	989	6,213
2020	−0.032	0.013	−0.012	0.007	−0.017	0.006	500	3,371

Notes: Displays gender hiring wage gap estimates by year, as per Appendix Figure C1 and corresponding to the regression models in Table 3 columns (I), (III) and (IV), respectively. ‘Coeff.’ shows the coefficient estimates and ‘s. e.’ the standard errors, robust to firm-occupation-year clusters.

TABLE B9: Estimation results for the gender hiring wage gap within jobs: professional vs non-professional jobs and collective bargaining agreements

Coefficient	Non-prof. (I)	Prof. (II)	No coll. ag. (III)	Coll. ag. (IV)
1. Female ($\widehat{\gamma}$)	-0.0254^{***}	-0.0495^{***}	-0.0291^{***}	-0.0441^{***}
	(0.0070)	(0.0066)	(0.0066)	(0.0080)
2. Age	0.0013^{**}	0.0030^{***}	0.0011^{**}	0.0018^{***}
	(0.0005)	(0.0005)	(0.0005)	(0.0006)
3. Age×Female	-0.0012^{**}	-0.0021^{***}	-0.0008	-0.0017^{**}
	(0.0006)	(0.0006)	(0.0006)	(0.0007)
4. Age^2 (00s)	-0.0095^{***}	-0.0196^{***}	-0.0119^{***}	-0.0128^{***}
	(0.0032)	(0.0026)	(0.0030)	(0.0035)
5. Age^2×Female (00s)	0.0033	0.0139^{***}	0.0062	0.0108^{**}
	(0.0042)	(0.0032)	(0.0036)	(0.0046)
6. Years employed	-0.0005	0.0020^{*}	0.0021^{*}	-0.0011
	(0.0012)	(0.0012)	(0.0013)	(0.0013)
7. Years employed×Female	0.0007	-0.0019	-0.0016	0.0007
	(0.0016)	(0.0015)	(0.0016)	(0.0018)
8. Years employed^2 (00s)	-0.0097	-0.0087	-0.0118	-0.0052
	(0.0091)	(0.0067)	(0.0086)	(0.0095)
9. Years employed^2×Female (00s)	0.0055	0.0084	0.0063	0.0110
	(0.0091)	(0.0067)	(0.0086)	(0.0095)
10. log(weekly hours)	-0.0315^{***}	-0.0052	-0.0051	-0.0436^{***}
	(0.0136)	(0.0077)	(0.0075)	(0.0150)
11. log(weekly hours)×Female	-0.0102	0.0023	-0.0096	0.0080
	(0.0146)	(0.0084)	(0.0097)	(0.0139)
12. Previous log(wage)	0.3100^{***}	0.0304^{**}	0.2378^{***}	0.1949^{***}
	(0.0162)	(0.0140)	(0.0189)	(0.0187)
13. Previous log(wage)×Female	-0.0319^{***}	0.0091	-0.0574^{***}	0.0010
	(0.0134)	(0.0156)	(0.0162)	(0.0161)
14. Previous tenure	-0.0012	-0.0013^{*}	-0.0027^{***}	-0.0006
	(0.0008)	(0.0007)	(0.0009)	(0.0008)
15. Previous tenure×Female	0.0016	0.0006	0.0025^{*}	-0.0003
	(0.0015)	(0.0010)	(0.0014)	(0.0014)
16. Previous full-time	0.0177^{**}	0.0126^{*}	0.0019	0.0193^{**}
	(0.0083)	(0.0066)	(0.0074)	(0.0084)
17. Previous full-time×Female	0.0036	0.0082	0.0281^{***}	-0.0148
	(0.0112)	(0.0089)	(0.0101)	(0.0109)
Constant	1.6032^{***}	1.7025^{***}	1.4849^{***}	1.8360^{***}
Firm-Year-Occupation FEs	✓	✓	✓	✓
R^2	0.831	0.527	0.810	0.840
N jobs	3,312	1,237	2,534	1,996
N hires	12,884	8,135	11,523	9,114

See Table 3 in the main text.
Column (I) uses only sample jobs that are in SOC 2000 or SOC 2010 categories 1-3 and not in SIC2003 categories G-H.
Column (II) only the sample jobs not used in Column (I).
Column (III) only uses sample jobs where pay was not determined according to some sort of collective agreement affecting more than one worker.
Column (IV) only uses sample jobs where pay was determined according to some sort of collective agreement.
***,**,* indicate significance from zero at 1%, 5% and 10% levels, respectively, two-sided tests. Standard errors in parentheses are robust to Firm-Year-Occupation clusters.

Appendix C. Additional Figures

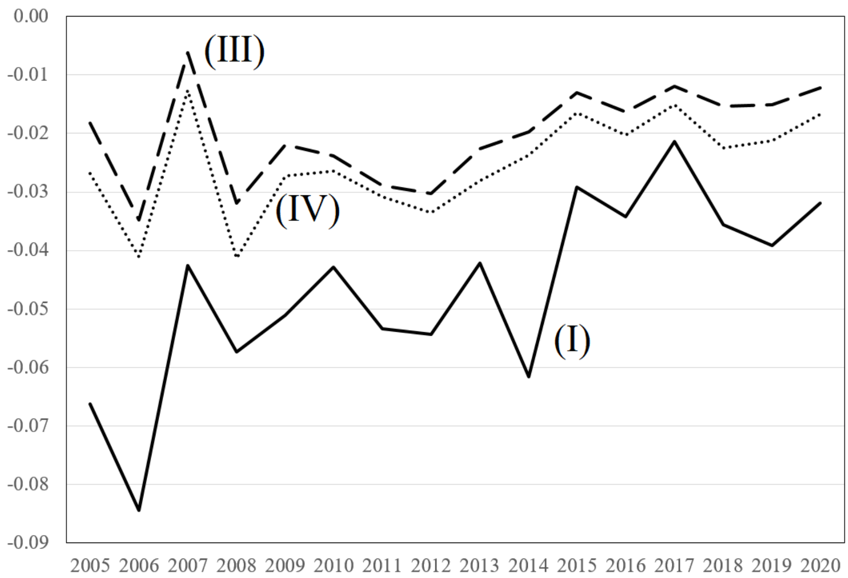

FIGURE C1: Estimates of the gender hiring wage gap by year

Notes: Series (I), (III), and (IV) display the hiring wage gap estimates ($\hat{\gamma}$) by year corresponding to the regression models in the main text Table 3, columns (I), (III) (IV), respectively. Appendix Table B8 contains the point estimates, associated standard errors, and sample dimensions.